

# Spatial Metadata for Remote Sensing Imagery

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**Abstract**—Mining the petabyte and growing archive of remotely sensed images to obtain the necessary information for land cover change studies becomes more difficult as more imagery is obtained and stored at various locations by government agencies or private companies. The increasing importance of networking with the requirement to move data sets between different servers and clients makes the data volume problem particularly acute. Mitigating this problem requires using data efficiently, that is, using data at the appropriate scale and resolution to adequately characterize phenomena, thus providing accurate answers to the questions being asked. This requires a thorough understanding of the effects of adjusting image resolution to match the resolution of images from other sources or supporting data for biophysical or urban growth models.

This paper summarizes a NASA Intelligent Systems-funded project that is examining the use of fractals and geostatistical techniques as aids to image classification and segmentation, as indicators of the effects of image processing techniques such as rectification, rescaling, ratioing and classification, as indicators for change detection, and as metadata for mining and selecting appropriate imagery for global change studies. This project will provide benchmarked indices of image complexity that complement existing metadata schemas and will facilitate image retrieval and analysis. This will streamline global change investigations by quickly identifying the proper source, lineage, general image content, scale, and resolution of imagery suited to an analysis of anthropogenic alterations in land cover, thus allowing researchers to concentrate on the underlying physical processes and potential consequences of these changes.

## I. INTRODUCTION

Satellite and aircraft-borne remote sensors have gathered huge volumes of data over the past 30 years. In the Earth Observing System (EOS) era, terabytes of image data are being archived every day [1]. These images are an important resource for establishing cause and effect relationships between human-induced land cover changes and alterations in climate and other biophysical patterns at local to global scales. However, the spatial, temporal, and spectral characteristics of these data vary, thus complicating long-term studies involving several types of imagery. This problem is particularly acute now that high-resolution commercial imagery and airborne scanner data

are available to researchers. As the geographical and temporal coverage, the spectral and spatial resolution, and the number of individual sensors increase, the sheer volume and complexity of available data sets will complicate management and use of the rapidly growing archive of earth imagery. Mining this vast data resource for images that provide the necessary information for climate change studies becomes more difficult as more sensors are launched and more imagery is obtained.

This project is examining the use of fractals, lacunarity, wavelets, geostatistical techniques such as spatial autocorrelation statistics, and landscape metrics such as contagion and Shannon diversity indices in measuring and characterizing land covers and land-cover changes with a variety of multi-scale, multi-temporal, and multi-sensor remotely sensed data. The purpose is to determine if these indices can be used to distinguish between landscapes that are captured in different spectral bands, pixel resolutions, and time periods. Particular emphasis is placed on evaluating how fractals, lacunarity, and other spatial indices behave in regions undergoing anthropogenic changes such as deforestation and urbanization. The outcome of this objective will be a set of global (i.e. whole image) measures that have been evaluated with respect to their accuracy and utility for inclusion in high-level, content-based searches of large image databases. Global measurement of the spatial characteristics of images are primarily used to provide indices and metadata for data retrieval and data mining.

To date, some of the spatial measurement techniques outlined above have also been applied to small areas defined by moving windows within the study areas [2] in order to explore the utility of the proposed techniques in characterizing landscapes, so that new algorithms for image segmentation and classification, texture characterization, and edge/pattern detection can be developed. This will increase the analyst's ability to detect subtle changes between images or to identify regions of interest that require more detailed investigation. The research and development of existing as well as new geospatial techniques for assessing land-cover change will be useful for regional as well as global environmental

monitoring. Gradual but consistent changes that are easily overlooked by human eyes or though traditional per-pixel image analysis techniques can more easily be detected through these spatial measurement techniques.

Scale and resolution effects on the spatial indices have been explored through simulated as well as real-world images [3]. Comparisons among the analytical techniques are being made to determine their utility in selecting the spatial characteristics of images used to measure and map phenomena, such as changes in lake and sea levels, urbanization [4], deforestation, and other land cover alterations. This will provide benchmarks for the accuracy and utility of spatial analyses as content-based indices of image complexity, as a basic means of segmenting images to highlight regions of interest, and as supplements to existing image classification techniques.

Multi-scale analyses of simulated and real-world image data provide a benchmark for determining the accuracy of the spatial indices of complexity. Multi-scale analysis using real image data provides further insights into the reliability of the various spatial indices in characterizing and segmenting different landscapes. The analysis of the effects of atmospheric correction, noise reduction, and contrast stretching on the indices helps determine what type and amount of image preprocessing is needed and whether raw remote sensing data can be used directly for change detection. As sensor resolutions increase in the NASA-EOS era and beyond, file sizes of these detailed images will limit the depth of possible analyses and will make imagery less portable unless rescaling techniques are employed to reduce the image resolution to a size appropriate to the physical phenomenon under investigation. The findings of this project could provide insights into the determination of the optimum resolution for analyzing a physical phenomenon by remote-sensing data.

## II. DATA MINING

The vast amount of information on the World Wide Web would be of little use without a means to locate information on topics selected by a user. Search engines that rely on keyword matches between the query and Web page titles or other indexed data are essential for successful use of this resource. Indexing multimedia data, such as imagery, videos, and audio files have proven to be problematic [5]. The many existing and potential uses for remotely sensed imagery make accessing images suited to a particular user's needs extremely complex and difficult. This complexity is exacerbated by sensor characteristics such as spatial, temporal, and radiometric resolution, which are often different for each sensor. The data indexing and search needs for global change investigations that seek to characterize anthropogenic impacts on climate, hydrology, and land cover are particularly demanding due to the range of data sets from old, low-resolution sensors

and new, high-resolutions sensors that must be merged in multi-temporal investigations [6].

Even seemingly simple searches for images depicting a particular location involve time-consuming analyses of the many individual scenes that have been gathered over the past 30 or more years, each having different sensor platforms, levels of quality (due to cloud cover, illumination, etc.), dates, and pre-processing. Metadata schemes such as the Earth Observing System Data and Information System (EOSDIS) Core Metadata Model (<http://ecsinfo.gsfc.nasa.gov>) address this to some extent by specifying location, lineage (including image processing and projection information), sensor characteristics, and other identifying keys to aid searches for images of specific areas at specific times. Ohm, et al., [7] characterize these as "high-level descriptors" which are generated when raw imagery is prepared for release. Mid-level descriptors include rule-based semantic identification of objects within a scene such as lakes, mountains, and vegetated areas. Low-level descriptors are image characteristics such as shape, color, pattern, and texture. By their nature, the mid- and low-level descriptors are often user-specific, and it would not be practical to add all of this information as formal metadata, since it is impossible to anticipate all uses to which an image may be applied.

It is becoming apparent that the common practice of using general metadata structures to access specific images is ineffective, thus pointing toward a need for intelligent image query techniques [8]. The MPEG-7 initiative aims to: a) create standards for the description of shape, color, and texture of objects depicted in audiovisual data, b) implement a description scheme, and c) provide ways of extending these descriptors and schemes via a specification language [9].

Given the difficulties of indexing and searching the content of images stored in data repositories, we propose a hierarchical approach that begins with the traditional high-level metadata items (such as location, date, sensor, etc), proceeds through customized mid-level searches of object identification (which would include items such as an assessment of whether the objects of interest are obscured by clouds), eventually followed by identification of images that depict the often small objects or subtle differences that are of interest in global change studies. The latter requires low-level descriptors that use geometric characteristics (such as size, shape, and orientation), radiometric characteristics that are analogous to the "color" descriptors in general image description schemes [10], and measures of texture and pattern to identify regions of interest to the user. Since the multi-spectral nature of most remotely sensed imagery has engendered an extensive list of tools for conducting radiometric investigations of images, the focus in this project on developing and evaluating indices of the spatial characteristics of either whole images in a global context or local subsets of images in the form of

fixed or moving windows. Since remotely sensed images of the earth's surface have few familiar objects that can be easily subsumed into semantic classes and categories, our approach emphasizes content-based techniques that operate primarily as low-level descriptors of texture, shape, and pattern.

### III. SPATIAL INDICES

Pixel-by-pixel image classification techniques that use the radiometric characteristics of a scene have been in use for a long time. Increasing attention has been made recently to include the spatial/textural relationships inherent in an image in classification. Spatial concepts such as size, shape, proximity, pattern and texture have only recently been incorporated into image classification procedures [11]. There are a number of indices that characterize the spatial structure of landscapes, including: contagion, dominance, and Shannon's diversity [12]. These indices are applicable to binary representations of landscapes that have been interpreted or classified. Many of these have been integrated into a software module called FRAGSTATS [13]. Other measures of spatial complexity such as fractals [14]-[15], local variance [16], and techniques that employ wavelets [17]-[18], can be applied directly to raw images without the need for classification or land-cover identification, thereby enabling change detection before user-assisted land-cover identification.

Analytical techniques in remote sensing that explicitly consider the spatial structure of imaged features have primarily been measures of image texture [19]-[20]. Texture represents tonal variations in the spatial domain and determines the overall visual smoothness or coarseness of the imaged features [21]. Gray-tone spatial-dependence or co-occurrence matrices provide the basis for a number of texture measures including range, variance, standard deviation, entropy, or uniformity within a moving window. These measures have been shown [22] to be a potentially useful means for image classification. Reference [23] proposed a geostatistical working definition of texture based on the variogram function to improve the performance of pixel-by-pixel classifiers. An increase in overall accuracy was achieved by considering the pixel to be spatially autocorrelated with its neighbors and by introducing this dependence numerically into the classifier as texture descriptors.

The application of geostatistics to remote sensing appears to offer great potential for analyzing multi-scaled data collected at different space, time and radiometric resolutions [24]. In its "purest" sense, *geostatistics* relate to statistical techniques that explicitly consider spatial autocorrelation by means of correlograms or variograms [25]. These are important tools for analyzing processes with continuous spatial indices; i.e., where the data represent spatio-temporal processes that occur continuously across or throughout a domain or region.

From this purview, geostatistics may be particularly useful for characterizing and visualizing the state, distribution, pattern, and arrangement of landscape attributes and processes as manifested in multi-scale remote sensing data.

Fractal analysis [14] provides tools for measuring the geometric complexity (number of discrete objects, perimeter to area ratios, and degree of spatial autocorrelation) of imaged objects. Complexity is represented in terms of the fractal dimension, a non-integer value that ranges from 2.0 in the case of a perfectly flat image to 3.0 for a very rough surface that essentially fills a volume. There has been a great deal of interest in this technique to model anthropogenic and naturally occurring phenomena [26]-[30]. There can be several features in an image that have different textures but share the same fractal dimension (in remote sensing, an expression of surface complexity). Lacunarity, which describes the departure from translational invariance, together with fractal dimension, can distinguish between these different sets [14], [31]-[32].

Multifractals are spatially intertwined fractals with a continuous spectrum of fractal dimensions [33]-[34]. Instead of a non-integer scalar describing the fractal dimension, complexity in a multifractal set is represented as either a continuous function of dimensions or possibly as a combination of two or more discrete multifractal dimensions [33]. Lacunarity in multifractals is also defined as a function and not as a scalar, and, as in the case of monofractals, it is separate and distinct from the multifractal dimension function [34]. Reference [35] examined the use of multifractals in characterizing the scale invariance of phenomena such as topography, clouds, and magnetic anomalies, depicted at different sensor resolutions.

Spatial autocorrelation of raster images can also be characterized by join count statistics such as Moran's  $I$  and Geary's  $C$  [38], which reflect the differing spatial structures of the smooth and rough surfaces. Moran's  $I$  varies from +1.0 for perfect positive correlation (a clumped pattern) to -1.0 for perfect negative correlation (a checkerboard pattern). Geary's  $C$  contiguity ratio, another index of spatial autocorrelation is similar to Moran's  $I$  but normally ranges from 0.0 to 3.0, with 0.0 indicating positive correlation, 1.0 indicating no correlation, and values greater than 1.0 indicating negative correlation.

These techniques (e.g. fractals, lacunarity, and spatial autocorrelation) are useful in image analysis primarily because they have sound mathematical bases. Moreover, they can be applied directly to raw images without the need for classification or land-cover identification, thereby enabling their use as content-based data mining tools.

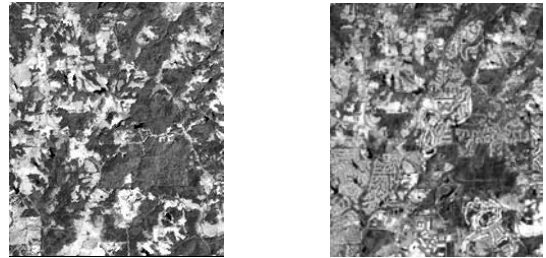
Problems that arise when using multi-temporal remote-sensing data for change detection include radiometric differences between images of different dates, pixel misregistration, the lack of appropriate data for earlier dates, the need to integrate multi-scale and multi-sensor

data, and the lack of assessment of the results. The most commonly used digital methods for change detection include post-classification comparison, image differencing, image ratioing, image regression, principal components analysis, and change vector analysis [19]. A major problem is that different studies utilizing different methods lead to different results. For example, [39] quantitatively compared methods for examining shifting cultivation in the tropical forest environment of India and found that the simple image differencing performed better than the more sophisticated principal components analysis technique. Reference [40] reviewed several techniques to monitor coastal changes. The authors found that principal components analysis combined with unsupervised classification of the component image gave good results. On the contrary, in a study of forest fires, [41] found that principal components analysis combined with unsupervised classification is not as satisfactory as the ratioing method. The increasing number of change-detection studies being reported in the literature since the late 1980s (e.g., [40]) indicates clearly the need for development of better techniques for change detection.

#### IV. CONTENT-BASED IMAGE DESCRIPTORS

In a poster presentation for the October GIS 2002 conference in Boulder, Colorado [4], fractal dimension was used as a content-based descriptor of image complexity. Atlanta, Georgia's rapid population increase from 1990 to 2000 provided a case study for evaluating the performance of this index. Census counts of population by census tract were interpolated to quarter-quadrangle sized areas using a volume-preserving overlay method. Georectified 10 m SPOT (tm) panchromatic imagery from 1990 was resampled to 15 m resolution and subsetting to the quarter quadrangles. 15 m Landsat ETM+ panchromatic imagery from 2000 was also subsetting to the same quadrangles. Global (whole image) fractal dimension measurements of the image subsets were obtained using the triangular prism method [43]-[44].

A spatial regression of the 1990 SPOT fractal dimension values versus the 2000 ETM+ fractal dimension measurements was performed and the residuals from this regression were used in a subsequent regression against 1990 - 2000 population growth, based on the idea that areas having the biggest differences between measured and modeled image complexity are areas that have experienced significant anthropogenic alterations to the land cover. This model yielded a relatively low agreement between the residuals and the interpolated population growth ( $R^2 = 0.37$ ), which was not surprising, considering the overly simplistic model and the fact that urban land cover change can lead to both simpler and more complex surfaces. This difference in complexity depends on the spatial extent of land clearance, building or road construction, or other alterations as compared to the resolution of the sensor.



a. Duluth NE Quarter Quadrangle 1990 Spot<sup>tm</sup> Panchromatic      b. Duluth NE Quarter Quadrangle 2000 Landsat ETM+ Panchromatic

Fig. 1. Quadrangle Having Maximum Difference in Fractal Dimension

As a search tool, however, fractal dimension proved to be helpful in identifying areas of the city that had undergone significant land cover alteration as evidenced by changes in population. The pair of images in Figure 1 had the biggest difference in fractal dimension between 1990 and 2000 and it is clear that extensive urbanization did occur in this time frame. Areas of the city that did not undergo significant growth in this time frame had similar fractal dimension values on the two dates.

#### V. SPATIAL RESOLUTION

The effects of resampling 1 m resolution Ikonos imagery [43] and 15 m resolution Landsat 7 ETM+ panchromatic images to coarser resolutions illustrate the utility of fractal dimension in determining optimal pixel size. The high-resolution image in Fig. 2a. shows details such as automobiles on the highways, individual trees, and air conditioning equipment on the roofs of industrial facilities that are not visible in the ETM+ image (Fig. 2b.) or the resampled Ikonos image (Fig. 2c.). These features are composed of relatively homogeneous blocks of similar pixel values. Fig. 3 shows that resampling to coarser resolutions leads to a rapid increase of fractal dimension, indicating a rougher surface with light and dark areas closely adjacent. At 8 m resolution, cars, trucks, and individual trees are no longer visible, and the increase in fractal dimension levels off. Beyond 16 m resolution, the fractal dimension increases, and continues up to a sill at approximately 60 m resolution. This pattern is also reflected in the ETM+ image, although lower contrast and fewer shadows in the Landsat image lead to lower fractal dimension values.

#### VI. LOCAL MEASURES OF IMAGE COMPLEXITY

When measured in overlapping and non-overlapping subsets of a remotely sensed image, Moran's I index of spatial autocorrelation and fractal dimension provide both a means for content-based image segmentation and edge detection. The problem of characterizing the spatial extent of urban development was used as an example of the

utility of local measures of these indices in both a single-band image segmentation context and as an additional layer for spectral/spatial image classification. The discussion in this section is based on a poster presentation at the December, 2002 American Geophysical Union Annual Meeting in San Francisco, California [46].



a. IKONOS 1 m Pan



b. Landsat ETM+ 15 m Pan



c. IKONOS 16 m Pan

Figure 2. IKONOS and Landsat Images of NW Atlanta Quarter Quadrangle

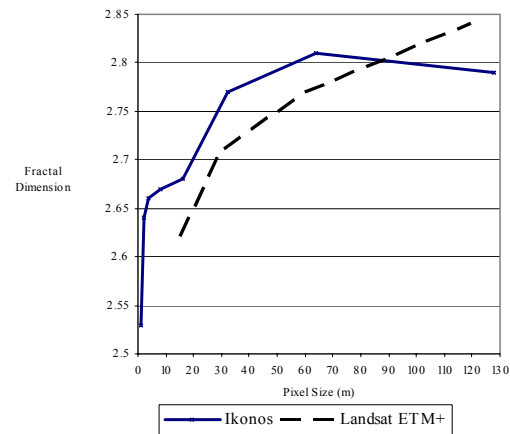


Fig. 3. Resampling Effects on Fractal Dimension of Atlanta Images

The area around Traverse City, Michigan at the southern end of Grand Traverse Bay was used to compare fractal dimension and Moran's  $I$  to Census block group-level indicators of urban development, such as total population, total housing units, and street density (total length of streets within a Census block group). The local fractal dimension and Moran's  $I$  indices were evaluated using Landsat 5 Thematic Mapper imagery from November 1, 1990 and Landsat 7 Enhanced Thematic Mapper Imagery obtained on October 19, 2000. Fig. 4 shows the result of computing fractal dimension of the 15 m resolution Landsat ETM+ pan image within a 21 x 21-pixel moving window incremented by 11 pixel steps. The red areas indicate zones of higher geometric complexity. The overlay of municipal boundaries indicates that highly complex urban areas tend to stand out from simpler natural backgrounds, although areas with high topographic relief and complex forested land covers also generate high fractal dimensions.

Non-overlapping 11 x 11 pixel windows generated images segmented according to their fractal dimension or Moran's  $I$  values. The zonal mean values were computed for each Census block group and compared to the corresponding indicators of urban development. As indicated in the correlation matrix (Table 1), zonal mean Moran's  $I$  values for the block groups were significantly correlated with the 2000 population and housing counts and was also significantly correlated with block group street density. Differences between the 1990 and 2000 local Moran's  $I$  values were significantly correlated with the number of new housing units.

TABLE 1  
CORRELATION MATRIX FOR MICHIGAN LANDSAT IMAGE

		Fractal Dimension	Moran's I	2000 Pop.	2000 Housing Units	Street Density
Fractal Dimension	Correlation	1.00	0.323	0.356	0.231	-0.113
	Significance	.	0.108	0.074	0.257	0.584
Moran's I	Correlation	0.323	1.000	-0.461*	-0.501**	0.740**
	Significance	0.108	.	0.018	0.009	0
2000 Pop.	Correlation	0.356	-0.461*	1.000	0.950**	-0.602
	Significance	0.074	0.018	.	0	0.001
2000 Housing Units	Correlation	0.231	-0.501**	0.950**	1.000	-0.584**
	Significance	0.257	0.009	0	.	0.002
Street Density	Correlation	-0.113	0.740**	-0.602	-0.584*	1.000
	Significance	0.584	0	0.001	0.002	.

\*Significant 2-tailed correlation at 0.01

\*\*Significant 2-tailed correlation at 0.05

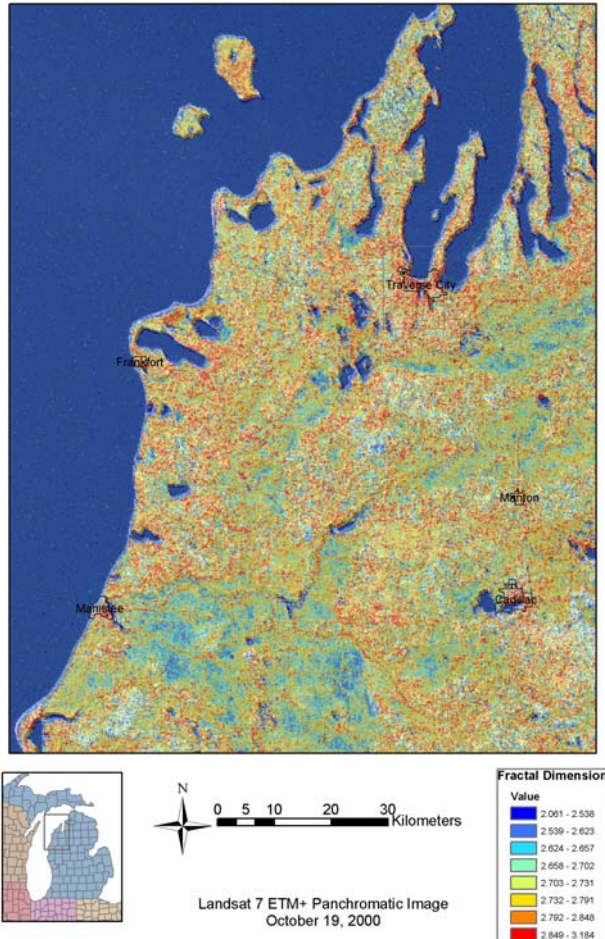


Fig. 4. Local Fractal Dimension of Traverse City, Michigan Area

## VI. MULTISCALE MODELING

Multiscale modeling has long been an issue in environmental research involving spatial data, as environmental and ecological phenomena are scale dependent in nature [47]. The scale issue is especially acute in the context of global change studies because of the need to integrate remote-sensing and other spatial data that are collected at different scales and resolutions. Extrapolation of results across broad spatial scales remains the most difficult problem in global environmental research [48]-[50]. There is a need for basic characterization of the effects of scale on image data, and the techniques used to measure these effects must be developed and implemented to allow for a multiple scale assessment of the data before any useful process-oriented modeling involving scale-dependent data can be conducted [51]-[52]. Preliminary results [53] show that changes in fractal dimension of images that are resampled to coarser resolutions indicate the optimum pixel size needed to observe physical phenomena that operate at characteristic spatial scales.

## VII. CONCLUSIONS

The rapid growth in the number of sensors and the exponential growth in the size and complexity of image databases points toward the need for content-based metadata for use in mining this resource. Content-based image descriptors can facilitate searches of imagery databases, although multi-spectral techniques are still needed to accurately classify urban land covers. Choosing the appropriate spatial scale for an analysis is crucial to understanding how local events and processes influence the whole Earth system. Image descriptors such as fractal

dimension can be added as Product Specific Attributes to the EOSDIS Core Metadata Model, and as such, they may be a helpful tag in mining large imagery databases. However, a single number cannot adequately characterize an entire scene, thus necessitating a pyramid approach that offers spatial index calculations at a range of resolutions and sizes of image subsets. Benchmarking these indices as they relate to global change studies can lead to a better understanding of the implications of comparing older, low resolution imagery to newer, high resolution images.

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